IJMST

**ISSN: 0974-5343**

**IJMST (2008), 1(1):13-21**

# An Automatic Sleep-Stage Classifier Using Electroencephalographic Signals

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**ABSTRACT:**

In this paper it has been developed a new method to classify sleep-stages using only Electroencephalographic signals. It combines Wavelet, Spectral Analysis, Neural Network and Euclidean distances in order to classify sleep epochs in three categories: Awake, REM/S1/S2 and S3/S4. The sleep classification process can be divided into six steps, EEG Filtering, Temporal Segmentation, Feature Extraction, Epoch Classification, Final Classification and Erroneous Epoch Correction. The classification method was tested in 12 EEG records obtained from the MIT-BIH Polysomnographic Database. Each 30s EEG segment was classified with the automatic method and compared with the real score given by a medical expert at the database. The Awake category had 83,4 %, the REM/S1/S2 had 37,8% and the last one had 60,0% of success results. The obtained results show that the proposed method provides a preliminary classification of sleep stages using only EEG signals.

**KEYWORDS**: Classification, EEG, Hypnogram, Sleep-stage.

## I. INTRODUCTION

Sleep is an integral part of the overall physical and mental well-being. Adequate sleep is essential to daytime alertness and optimum function. It has a vital role in the regular functioning of the nervous system and allows a person to function both physically and mentally. Sleep is an essential requirement for the normal functioning of the body's immune system and ability to fight disease and sickness. There are many sleep disorders, like insomnia, narcolepsy, sleep apnea and many others that manifest themselves through sleep disturbances (e.g., depression, schizophrenia, Alzheimer disease, etc.) [1].

In general, sleep stages are analyzed in 30s long epochs from polysomnographic records, thereafter, they are classified by an expert to manually obtain the hypnogram. In order to improve this procedure, it is important to develop new methods based on signal processing techniques with the purpose of supplying visual classification.

The main states are wakefulness, REM (Rapid Eye Movement) sleep and Non-REM sleep. Non-REM sleep is further divided into four stages, from the lightest Stage 1 to the deepest Stage 4. Stages 3 and 4 are referred to as slow wave sleep (SWS). The frequency of sleep stages alters during the night; in the early hours of sleep, SWS dominates, whereas REM sleep occurs more often in the second part of sleep. In a healthy subject, 75 % of night dream is No-REM and the other 25 % is REM. The features of the electroencephalogram (EEG), electromyogram (EMG) and electrooculogram (EOG) for each sleep stage are detailed in Table I [2].

Table I. Features of EEG, EMG and EOG signals for each sleep stage

| | |
|---|---|
| Awake | EEG: ***Beta*** (12-30 Hz) ***Alpha*** **( 8-12 Hz)**<br>EMG: muscular activity<br>EOG: Fast movement |
| Stage 1 | EEG: ***Theta*** (4-8 Hz).<br>EMG: Less activity than Awake<br>EOG: Slow movement |
| Stage 2 | EEG: ***Picks*** (12-15 Hz). ***K Complex*** (1 Hz).<br>EMG: No Activity.<br>EOG: No movement |
| Stage 3 | EEG: ***Delta*** (1-4 Hz) 20 a 50 % of time.<br>EMG: No Activity.<br>EOG: No movement. |
| Stage 4 | EEG: ***Delta*** (1-4 Hz) more than 50 % of time.<br>EMG: Poor Activity.<br>EOG: no detectable movement. |
| REM | EEG : between Awake and Stage 1.<br>***Beta*** (12-30 Hz), ***Alpha*** **( 8-12 Hz)** and ***Theta*** **( 4-8 Hz)**<br>Sawtooth waves (3-5 Hz).<br>EMG: minimum activity.<br>EOG: Fast movement. |

Figure 1 illustrates the different sleep stages on several EEG segments. It can be observed that the frequencies of each piece are different and they are lower as the sleep stage gets deeper. Stages REM, S1 and S2 cover a similar frequency bandwidth, while stages S3 and S4 have the same frequency but the percentages of presence in the epoch vary. Such similar characteristics tend to confuse the classification process.

As a first task in sleep stage classification, epochs will be separated only in three categories using the similitude of the signals. Those categories are "Awake", "REM/S1/S2", and "S3/S4".

Sleep macrostructure evaluation can be based on assigning labels to the different epochs. One method is to show the different epoch stages as time series and plot them to get the hypnogram. Figure 2 shows an example of a hypnogram.

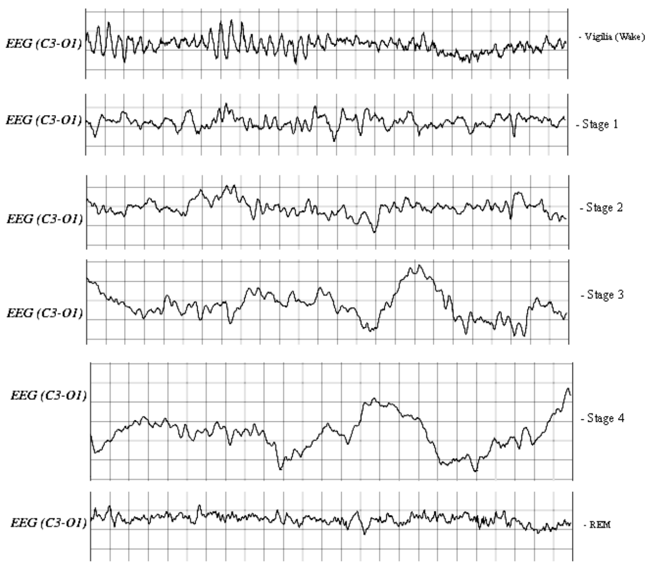


Figure 1. Sleep-stages epochs of an EEG recording with their corresponding labels.

In this study, an automatic sleep stage scoring method was developed using a single-channel EEG record. The method classifies 30 second epochs extracted from the signal. Each epoch was classified according to one of the three next following categories: "Awake", "REM/S1/S2" and "S3/S4". The proposed classification technique combines Wavelet Transform, Neural Network and Euclidean Distances and uses different features from time and frequency domains in order to assign a sleep-stage label to each epoch of the EEG records. The main advantage of the proposed method is that it makes use of just a single EEG channel; other signals (as EOG or EMG) are not necessary, thus, being simpler and more practical.

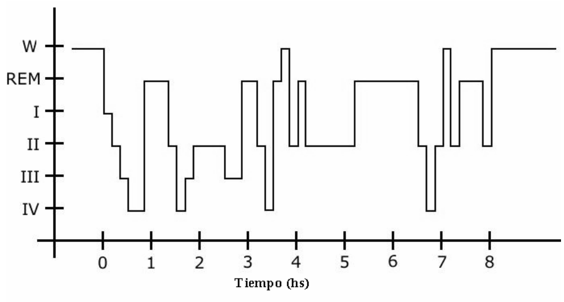


Figure 2. Example of a hypnogram.

## II. Materials

Sleep EEG records of twelve subjects were randomly selected from the MIT-BIH Polysomnographic Database. All subjects were male, aged 32 to 56 (mean age 43). This database contains over 80 hours of four-, six-, and seven-channel polysomnographic recordings, each with an ECG signal annotated beat-by-beat, and EEG and respiration signals annotated by an expert with respect to sleep stages and apnea [3]. Some of the patients of the database suffered some kind of sleep disorder. EEG signals were sampled with a resolution of 250Hz. The sleep stages were visually scored for 30 seconds epoch, according to the criteria of Rechtschaffen and Kales [4]. Each annotation applies to the thirty seconds of the record that *follow* the annotation.

## III. Methodology

In this study, EEG epochs were classified in one of three categories "Awake", "REM/S1/S2" and "S3/S4". The result was a stage-label for each 30s epoch.

The sleep classification process can be divided into six steps: *EEG Filtering, Temporal Segmentation, Feature Extraction, Epoch Classification, Final Classification and Erroneous Epoch Correction.* The block diagram of the proposed classification method is illustrated in Figure 3.

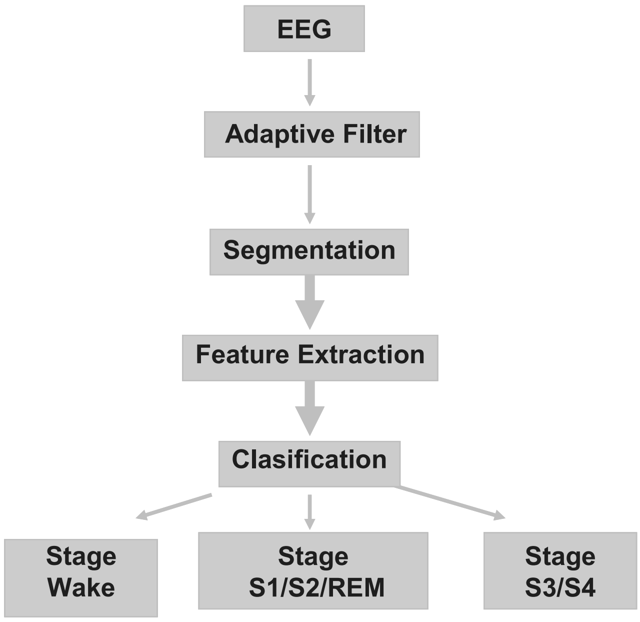


Figure 3. Block diagram of the proposed sleep-stage automatic classifier.

### A. EEG filtering

Neurological rhythms are generally mixed with other biological signals, as ECG and EMG, and corrupted with power line interference. In the proposed method, EEG records are firstly filtered with a previous algorithm developed by the authors [5] consisted of a cascade of three adaptive filters based on least mean squares (LMS). The first one eliminates power line interference, the second adaptive filter removes the ECG artifacts and the last one cancels EOG spikes. Figure 4 illustrates the scheme of the cascade of adaptive filters.

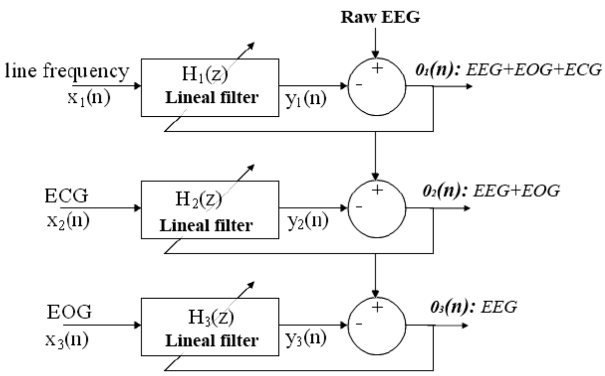


Figure 4. Scheme of the cascade of adaptive filters.

In this work, the third adaptive filter it is not used because it is important to preserve the EOG artifacts mixed in EEG record in order to recognize REM stages, which is characterized by rapid eyes movements. For this reason, it was employed the output signal of the second adaptive filter.

Figure 5 shows an example of a raw EEG record (Fig. 5.a) and its corresponding filtered signal after power line interference elimination (Fig. 5.b) and ECG artifacts cancellation (Fig. 5.c).

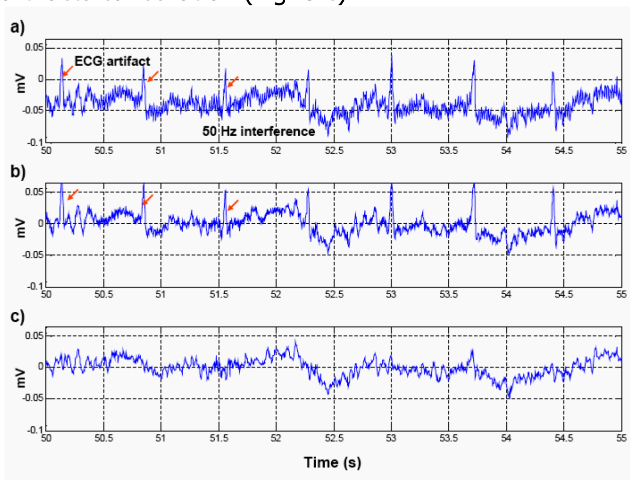


Figure 5. Example of EEG filtering. a) Raw EEG record, b) EEG signal after power line interference elimination, c) EEG with out ECG artifacts and 50 z interference.

### B. Temporal Segmentation

Extraction of characteristic parameters requires EEG segmentation. Herein, we make use of two segmentations.

In the first one, the entire EEG is divided in 30s long epochs. It is done so because the sleep annotations provided by the database are given in that time length. In the second segmentation, the 30s segments are split in six sub-matrices. The reasons for this segmentation are two: a) To improve statistical stationarity in order to be able to use methods in which the signal must meet such condition; and b) To increase the performance of the classifier by obtaining six partial conclusions from the same 30s epoch.

### C. Feature extraction

This step is the key of epoch classification. Different features have been obtained from wavelet decomposition and spectral analysis, as follows,

ISSN: 0974-5343
IJMST (2008), 1(1):13-21

1) *Wavelet decomposition*

After temporal segmentation, each 5s segment in each sub-matrix was decomposed using a wavelet transform (WT). This technique decomposes temporal signals in the time-scale plane and it has been used to study sleep stage characteristics [6].

The wavelet used herein was the quadratic spline Mallat type with compact support and one vanishing moment [7]. Its advantages include implementation by linear phase filters and signal decomposition that is shift-invariant across the different analysis scales. Due to these properties, this wavelet function has been previously used for processing other biomedical signals, for example, for the alignment of beats in high resolution ECG records [8] and for delineation of ECG characteristic points [9].

Figure 6 illustrates the filter-bank implementation of the quadratic spline WT by Mallat algorithm [7].

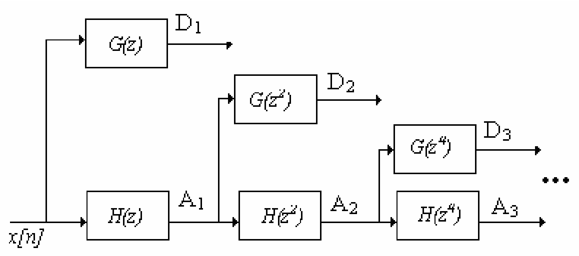


Figure 6. Filter-bank implementations of quadratic spline WT.

Eqn. 1 and 2 describe the frequency response of the filters H(n) and G(n) to implement the DWT (Discrete Wavelet Transform).

$$H(\omega) = e^{j\omega/2}\left(\cos\frac{\omega}{2}\right)^3 \quad (1)$$

$$G(\omega) = 4je^{j\omega/2}\left(\sin\frac{\omega}{2}\right) \quad (2)$$

The frequency responses of the signals Ak (Approximations) and Dk (Details) for the scales k=1..,6 are,

$$A'_k(\omega) = P_k(\omega)X(\omega) \quad (3)$$

$$D'_k(\omega) = Q_k(\omega)X(\omega) \quad (4)$$

where X(ω) is the Fourier transform of x(n) while Pk(ω) and Qk(ω) are the spectral transfer functions, respectively, of the equivalent filters for scales k=1..,6 of the signals Ak and Dk, that is.

$$P_k(\omega) = \prod_{m=0}^{k-1} H\left(2^m\omega\right) \quad (5)$$

$$Q_k(\omega) = G\left(2^{k-1}\omega\right)\prod_{m=0}^{k-2} H\left(2^m\omega\right) \quad (6)$$

The frequency responses of the equivalent low-pass and band-pass filters, $Q_k(\omega)$, $P_k(\omega)$, for the scales *k*=1,..6 (except $Q_1(\omega)$, which is a high-pass filter), considering a sampling frequency of 250 Hz, is illustrated in Figure 7. The -3dB cut-off frequencies values of $P_k$ and $Q_k$ equivalent filters for each of the decomposition scales are shown in Table II [7].

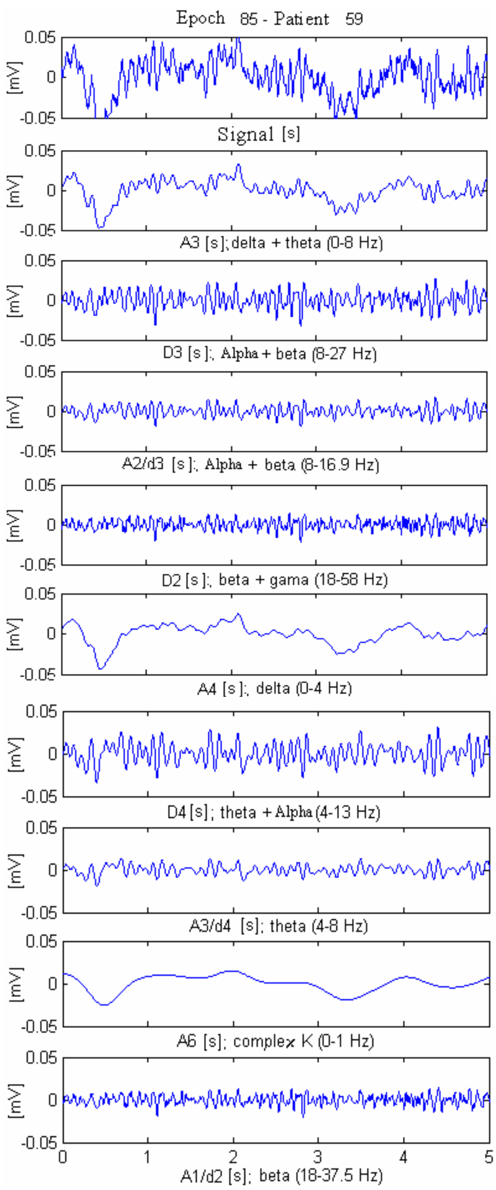


Figure 8: An example of 5s long epoch wavelet decomposition.

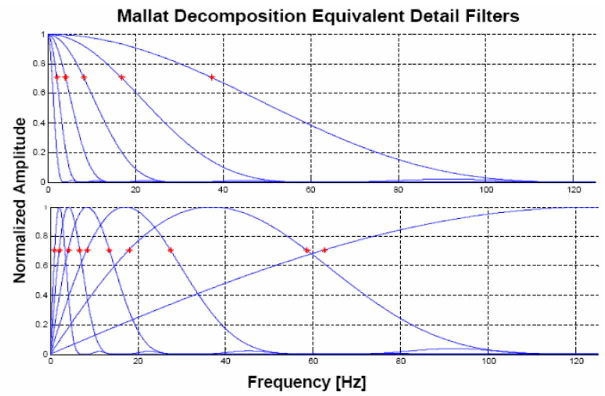


Figure 7. The response of frequency of the equivalent filters $P_k(\omega)$ and $Q_k(\omega)$ for scales $k$=1..,6 and a sampling frequency of 250 Hz.

Table II. The -3dB cut off frecuencies values of $P_k$ and $Q_k$ equivalent filters

| Scale | $P_k$ | $Q_k$ | |
|---|---|---|---|
| | Fc(Hz) | Fc(Hz) | Fc(Hz) |
| 1 | 37.55 | 62.5 | - |
| 2 | 16.9 | 19.02 | 58.6 |
| 3 | 8.25 | 8.35 | 27.45 |
| 4 | 4.125 | 4.1 | 13.52 |
| 5 | 2.05 | 2.05 | 6.75 |
| 6 | 1.03 | 1.03 | 3.37 |

Some detail ($D_k$) and approach ($A_k$) signals were particularly selected to extract spectral features from the EEG records. Table III shows the nine decomposition signals selected and their corresponding -3dB bandwidths.

Table III. Bandwidths of each signal

| Signal | Bandwidths |
|---|---|
| A4 | 0-4 Hz |
| D4 | 0-14 Hz |
| D3 | 8-27 Hz |
| D2 | 18-58 Hz |
| A3 | 0-8 Hz |
| A3-D4 | 4-8 Hz |
| A2-D3 | 8-17 Hz |
| A6 | 0-1 Hz |
| A1-D2 | 18-37 Hz |

Figure 8 displays an example of wavelet decomposition of a 5s long EEG epoch.

After signal decomposition, several statistical parameters (mean amplitude, range, standard deviation, maximum amplitude and minimum amplitude, RMS value) were extracted from different levels.

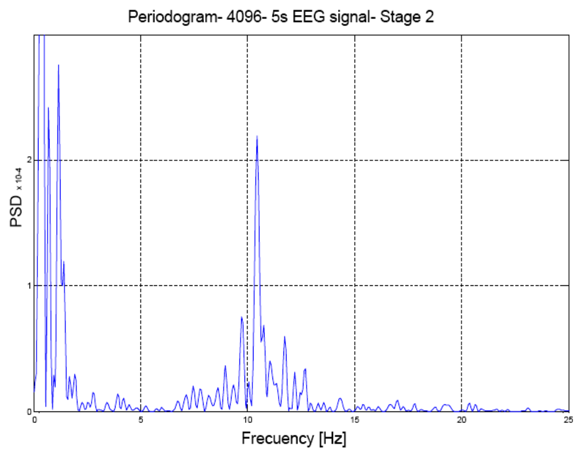


Figure 9. Power spectral density for a 5s EEG segment during stage 2.

2) *Spectral analysis*

The power spectral density (PSD), for each 5s EEG segment and also for each of the six matrices constructed before, were obtained. For that matter, the conventional periodogram was used with a rectangular window and 4096 points. Thus, a good relationship between spectral dispersion and resolution is kept.

Figure 9 shows an example of PSD for a 5s EEG segment during Stage 2. It could be observed that characteristic rhythms of this stage, like as picks (12-15 Hz) and K complex (1 Hz), are present at the signal. Those spectral characteristics are relevant for the further recognition of Stage 2 EEG segments.

Some other features were extracted from each segment frequency spectrum, such as maximum power density, frequency at the maximum power density, accumulated and relative power density and the standard deviation of power density in each frequency band (*Betha, Alpha, Theta, Deltha*).

*D. Epochs Classification.*

Four classifiers were used in the proposed method. Each has the particularity of identifying some sleep-stage better than others. The combination of them gives better results than each individually. These classifiers are: *Neuronal network, Euclidean Distances to two different pattern vectors, Rules based on spectral characteristic values.*

*1) Neuronal Network, memory-based learning.*

A neural network (NN) is an interconnected group of artificial neurons that uses a mathematical or

computational model for information processing based on a connectionist approach to computation. In most cases, a NN is an adaptive system that changes its structure based on external or internal information that flows through the network.

In more practical terms, neural networks are non-linear statistical data modeling or decision making tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data [10].

In this paper, it is proposed a NN as first classifier. Particularly, it is used a neural network memory-based learning, where most of the past experiences are explicitly stored in a large memory of correctly classifier input-output examples [10]. The dimensions memory matrix are 3 x 50, the input vector (50 x 1) is arranged with different statistical parameters values and spectrum features. The output vector (3 x 1) has a higger value near to the unity at the first, second or thrird position depending of the chooseen categories, while the other two have lower values near to zero. The training is done with vectors of statistical parameters values and spectrum features, up to that the error is enough low.

The NN was trained with vectors based on the characteristics of two EEG records, namely patients 4 and 59. Those patients were chosen among others because their records have very notable sleep stages features.

After training, the NN is used to classify each 5s long segment in one of the three categories mentioned before: Awake, REM/S1/S2 or S3/S4. It has been noted that the NN as first classifier is very reliable in the classification of the "Awake" stages.

*2) Euclidean Distances to pattern vector a)*

In this classifier, Euclidean distances were used. A pattern vector of spectrum features was constructed with epochs of patients 4 and 59. Their median and the mean values were used to get the pattern vector of each category. To classify a segment, the smallest Euclidean Distance is searched from each pattern vector. The Euclidean distance is defined in (7) as,

$$Ed = \left\| y_{rk} - y_{d_k} \right\| = \sqrt{\sum_{k=1}^{m} \left( y_{rk} - y_{d_k} \right)^2} \qquad (7)$$

where $y_{rk}$ is the 5s long segment to classify, $y_{dk}$ is the pattern vector and $k$= 1,2,3 corresponds to the three categories.

*3) Euclidean Distances to pattern vector b)*

In this classifier a pattern vector of statistical parameters was constructed with epochs of patients 4 and 59. The method is the same as in the step before but with statistical parameters values instead of spectral feature values.

It has been observed that the second and third classifiers are reliable classifying "REM/S1/S2" segments.

*4) Rules based on spectral characteristic values*

Some spectral characteristic values of each stage-epoch were obtained. The maximum values in each band-width are characteristic of each category. For example, the maximum values for the awake-epoch are in the *Betha (12-30 Hz)* and *Alpha (8-12Hz)* bands. Thus, based on the position of the maximum values in the frequency domain, some rules were used to classify the segments. This classifier is very reliable in the classification of the "S3/S4" stages.

*E. Final Classification.*

This final classification has two steps. In the first one, four decisions are taken from the 24 results obtained in the previous steps (four decisions per each of the six 5s long segment matrices). The winning category is that which has the bigger percentage of label presence in the six matrices. Four possible results are obtained for each 30s long epoch.

In the second step, a final decision is taken based on the four previous ones. This decision in based on the classifier characteristics to identify one category better than the others. In this part of the algorithm all the 30s long epochs have a stage-label.

IJMST

**ISSN: 0974-5343**
**IJMST (2008), 1(1):13-21**

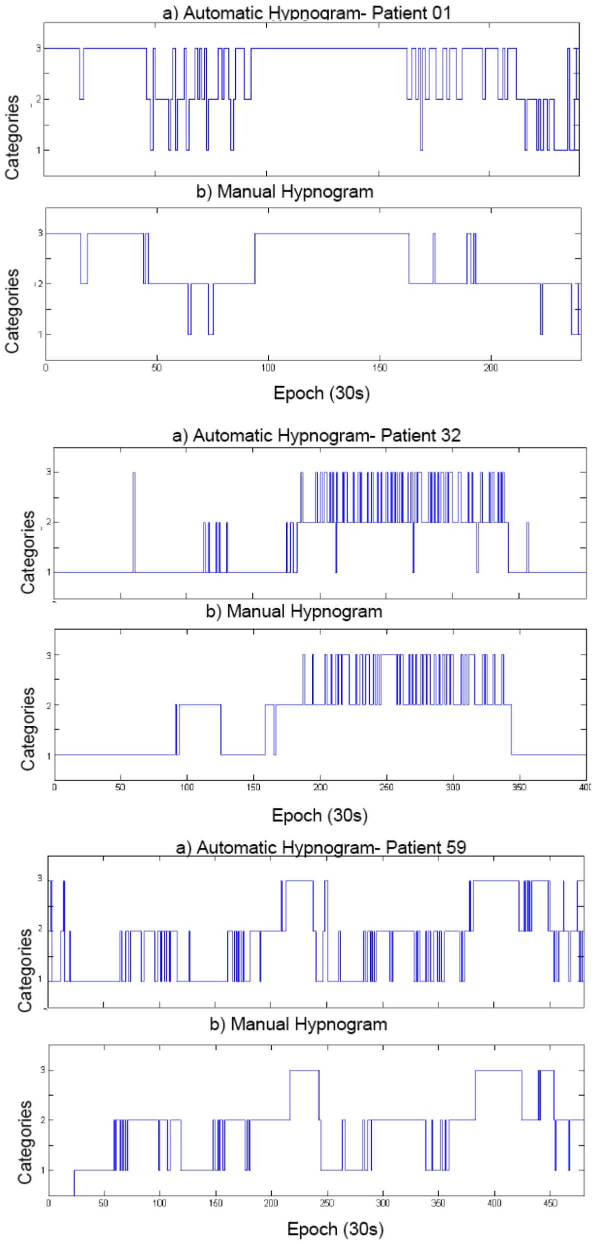


Figure 10. Comparison between Automatic and manual hypnogram of patients 1, 32 and 59.

### F. *Erroneous epoch correction.*

This correction is based on the impossibility of occurrence of certain transitions among sleep stages [11]. For example, it is impossible a transition from the "Awake" stage to the "S3" and "S4" stages, without passing through REM, S1 or S2 sleep stages. Other similar impossible transitions were used to correct erroneous epochs.

## IV. RESULTS

The automatic classification method proposed in this paper gives a label for each EEG 30s epoch. The three labels are: *"Awake", "REM / S1 / S2" and "S3 / S4".* The first category corresponds to the epoch of the awake-stage. All epochs from REM-Stage, Stages 1 or 2, have the second category label and epochs that correspond to the Stages 3 or 4 have the third category label.

Figure 10 shows the hypnograms obtained by the automatic method (above) and the manual classifier (below) for patients 1, 32 and 59. The whole sleep period has been divided into epochs of 30s with one of the three classify-labels. Ordinates "1" correspond to awake-Stage, Ordinates "2" to the "REM / S1 / S2" category, and the "3" to the "S3 / S4" category. Those hypnograms don't discriminate individual sleep stages; they have been classified in the three mentioned categories. It can be observed that manual and automatic hypnograms are qualitatively similar.

In order to obtain quantitative results, it was computed the percentages of success results for each category grouped together per patient. These results are shown in Figure 11 and presented in Table IV. The last one summarizes the successes for each twelve patients, the total number of stages present in all categories and the percentage of satisfactory results. In general, the "Awake" category was classified with an 83.4% success, "REM/S1/S2" category was classified with a 37.8% and the "S3/S4" category came up with a 60.0% success.

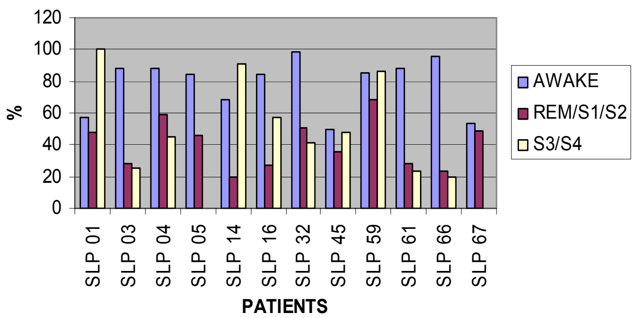


Figure 11. Percentages of successes results grouped together per patients.

## V. DISCUSSION AND CONCLUSIONS

In this paper, it has been developed a new method

Table IV. Percentages of successes results of each patients and each sleep category.

| | AWAKE | | | REM /S1/ S2 | | | S3/S4 | | |
|---|---|---|---|---|---|---|---|---|---|
| ***PATIENT*** | SUCCESSES RESULT | TOTAL STAGES | % | SUCCESSES RESULT | TOTAL STAGES | % | SUCCESSES RESULT | TOTAL STAGES | % |
| ***slp01*** | 4 | 7 | 57,14 | 57 | 120 | 47,50 | 115 | 115 | 100,00 |
| ***slp03*** | 54 | 61 | 88,52 | 81 | 284 | 28,52 | 14 | 56 | 25,00 |
| ***slp04*** | 128 | 146 | 87,67 | 197 | 332 | 59,34 | 10 | 22 | 45,45 |
| ***slp05*** | 152 | 180 | 84,44 | 82 | 180 | 45,56 | 0 | 0 | - |
| ***slp14*** | 221 | 321 | 68,85 | 70 | 350 | 20,00 | 38 | 42 | 90,48 |
| ***slp16*** | 249 | 296 | 84,12 | 95 | 351 | 27,07 | 13 | 24 | 54,17 |
| ***slp32*** | 182 | 185 | 98,38 | 78 | 155 | 50,32 | 25 | 60 | 41,67 |
| ***slp45*** | 1 | 2 | 50,00 | 72 | 203 | 35,47 | 60 | 125 | 48,00 |
| ***slp59*** | 119 | 140 | 85,00 | 162 | 238 | 68,07 | 69 | 80 | 86,25 |
| ***slp61*** | 79 | 90 | 87,78 | 77 | 275 | 28,00 | 18 | 76 | 23,68 |
| ***slp66*** | 167 | 174 | 95,98 | 60 | 259 | 23,17 | 1 | 5 | 20,00 |
| ***slp67*** | 37 | 69 | 53,62 | 39 | 80 | 48,75 | 0 | 0 | - |
| ***All*** | **1393** | **1671** | **83,4** | **1070** | **2827** | **37,8** | **363** | **605** | **60,0** |

to classify sleep-stages using only EEG signals. The method classifies 30 second EEG segments in one of three categories: "Awake", "REM/S1/S2" or "S3/S4".
After EEG filtering and segmentation processes, it is used wavelet transform and spectral analysis in order to extract different temporal and spectral features from the EEG record. The feature extraction in temporal and frequency domains is a fundamental step to obtain good results at the final classification phase.
The Wavelet Transform (WT) is a great utility technique for the separation of the cerebral rhythms.
The diverse cerebral rhythms of sleep stages are included in the nine decomposition levels of WT used in this paper. The analysis of each one of those decomposition signals gives some temporal parameters which characterized each one of the sleep categories.

In order to obtain the frequency representation of the EEG signal, it was chosen the conventional periodogram with a rectangular window and 4096 points. With this selection, a good relationship between spectral dispersion and resolution was kept.
After feature extraction, different techniques were used as classifiers for sleep categories: Neural Networks (NN), Euclidean Distances to two different pattern vectors, Rules Based on spectral characteristic values.
The NN is a good classifier for this kind of problem. It is able to create patterns based on some records and to use them to classifier and to identify segments and epochs that belong to a new patient. It has been noted that the NN as first classifier is very reliable in the classification of the "Awake" stages. In order to increase the performance of this classifier in the other sleep categories, it was added additional classifiers.
The classification with distances Euclidean based on pattern vectors improves the classification of "REM/S1/ S2" segments. Also using different rules based on spectral characteristic values it allows a very good identification of S3/S4 segments.

The proposed method classified correctly the 83.4%, 37.8%, and 60.0% of EEG segments corresponding to "Awake", "REM/S1/S2" or "S3/S4" categories, respectively. These results are acceptable as first estimation of real hypnograms. They are a good approximation, too, of the manual scored ones, as it can be seen in Figure 10. There are some differences in those parts where the stages change quickly, but in general, both functions are similar.

As it can be seen in Table IV, the second category has the lowest percentage of successes results. It is probably due to the REM stage is frequently confused with the Awake stage. They have similar cerebral rhythms, like as Alpha and Beta waves, as it can be observed in Table I. The main feature of REM stage is the presence of rapid eyes movement, which normally are recorded in EOG signals, but only they appears as artifacts in EEG records. Considering that only the EEG

signal have been used in this work, it can be considered that these results are very acceptable.

Figure 11 and Table IV show that the results of patients 4 and 59 are better than the others used in this work. It is due to that their records were used to train the NN and to obtain the spectral and statistical pattern vectors. However, the results for the rest of the patient are good. For example, the classifier is able to recognize the total S3/S4 epoch for the patient 1 and 182/185 awake segments belong to the patient 32. Those results show that the classifier is able to identify EEG segments and epochs that belong to new patients.

It has been concluded that the proposed method provides a preliminary classification of sleep stages using only EEG signals.

## ACKNOWLEDGMENTS

This work has been supported by grants from Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET) and Universidad Nacional de San Juan (UNSJ), both institutions from Argentina.

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